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Food Photo Recognition for Dietary Tracking: System and Experiment

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Abstract. Tracking dietary intake is an important task for health management especially for chronic diseases such as obesity, diabetes, and cardiovascular diseases. Given the popularity of personal hand-held devices, mobile applications provide a promising low-cost solution to tackle the key risk factor by diet monitoring. In this work, we propose a photo based dietary tracking system that employs deep-based image recognition algorithms to recognize food and analyze nutrition. The system is beneficial for patients to manage their dietary and nutrition intake, and for the medical institutions to intervene and treat the chronic diseases. To the best of our knowledge, there are no popular applications in the market that provide a high-performance food photo recognition like ours, which is more convenient and intuitive to enter food than textual typing. We conducted experiments on evaluating the recognition accuracy on laboratory data and real user data on Singapore local food, which shed light on uplifting lab trained image recognition models in real applications. In addition, we have conducted user study to verify that our proposed method has the potential to foster higher user engagement rate as compared to existing apps based dietary tracking approaches.

Keywords: Food image recognition · Dietary app · User food photo

1 Introduction

Chronic diseases such as diabetes, obesity, and cardiovascular diseases are becoming the dominant sources of mortality and morbidity worldwide and recently an epidemic in many Asia Pacific countries [4,25]. Unhealthy diet is one of the key common modifiable risk factors in preventing and managing chronic diseases [28]. Personalized dietary intake intervention showed significant impact on influencing

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people's choice and promoting their health [4]. The feedback on nutrition intake is substantial and behavioral changing when patients track their dietary intake for a considerable length of time. However, the burden of logging food makes compliance a challenge. Clinical studies rely on patients to recall dietary intake, which is time-consuming and prone to underestimation [18]. On the other hand, the ubiquitous usage of mobile devices makes it possible for one to track the dietary intake on personal devices. Indeed there are thousands of applications available on food logging and calorie counting. According to [3], people who self-track diet and lifestyle with mobile devices have experienced "strong behavior change".

The convenience of food entering methods plays a key role in the usability of dietary tracking applications [14]. Existing methods include food database search and free text diary, both requiring typing. Bar code scanning is efficient but limited to packaged food. The recent advancement in computer vision and deep learning makes photo based dietary tracking possible through automatic food image recognition [7,9,22,24]. Photo based dietary tracking is more intuitive, more faithful, and easier to perform than text based approaches [19]. To perform subsequent nutrition value analysis, the recognized food category is used to look up nutrition databases [24]. When a food type is not covered, nutrition can still be estimated by ingredient recognition [9].

Despite the enormous success of image recognition methods in recent years, their performance in a real dietary tracking system is relatively less explored. In this work, we propose to use photo taking and food image recognition as the dietary entering method. The following questions need to be answered:

1. Can the photo based dietary tracking method improve the efficiency and user satisfaction of food entering?
2. Does lab trained image recognition model suffice when applied in a real dietary tracking system?
3. In case there is substantially different in performance between the lab and the real usage settings, what are the underlying reasons? What are the actions to improve the real usage performance?

In this work, we built a photo based dietary tracking system named *DietLens* on mobile devices. We first experimented a deep-based food image recognition model in the lab on Singapore food, which has one of the most diverse food environment sharing influences from Chinese, Malay, Indian and Western cultures [18]. We then applied the recognition model in our prototype system, the *DietLens*. Through the prototype system, we tested the model on real user food images. Moreover, we conducted user study that compares the usability of several popular food tracking applications and our prototype system with focus on the food entering methods. The contributions of this paper are three folds:

– We have developed a dietary tracking mobile application, which has been shown to have higher usability than some of the popular applications.
– We experimented food image recognition on laboratory data and real user data, which sheds light on approaches to improve lab trained image recognition models on food recognition.

– Within the photo based tracking methods, we introduced a novel photo-based portion selection method, which has been verified scientifically in medical research and demonstrated empirically to be better than existing approaches.

2 Background and Literature Review

2.1 Deep-Based Food Recognition

Food recognition for health-oriented applications has started to capture more research attention in recent years. Existing works include simultaneous estimation of food categories and calories [10], multi-food recognition [23], context-based recognition by GPS and restaurant menus [6], multi-modal food categorization [15], and multi-task learning of food and ingredient recognition [9]. Owing to the success of deep learning technologies in image classification, most recent works employ deep features extracted directly from neural networks for image-level food categorization [16,29]. For example, [16] extract features from AlexNet [17], and then utilize SVM for food classification. The DCNN features perform significantly better than hand-crafted features. Similar conclusion is also reported by [7,9] on Food-101 and VIREO Food-172 data set respectively.

Different deep architectures have also been exploited for food recognition [9,12,20,21]. [9] modifies VGG for multi-task food and ingredient recognition; [12,20] exploit and revise inception modules while [21] modifies Residual Network (ResNet) [13] for food recognition. As reported in [9,21], deeper networks such as VGG, GoogleNet and ResNet tend to achieve better recognition performance than AlexNet.

2.2 Dietary Tracking Mobile Applications

There are many food tracking mobile applications, e.g., Foodlog [5,27], MyFitnessPal and FatSecret. To understand the available dietary tracking methods, we surveyed a number of food tracking mobile applications sorted by their popularity as shown in Table 1. We identify that food entering and portion size specification are two key steps in dietary tracking.

Table 1. Comparison of popular dietary tracking mobile applications. Note that the number of downloads is taken from Android Play Store because iOS App Store does not provide this number.

App name	Record by photo	Food photo recognition	Record by search	Record by barcode scan	Record by free text	Rating out of 5	# rating	Launch time	# download
MyFitnessPal	N	NA	Y	Y	Y	4.6	1,000,000	2005	50,000,000
FatSecret	Y	N	Y	Y	Y	4.4	193,000	2007	10,000,000
Noom Coach	N	NA	Y	Y	Y	4.3	166,000	2010	10,000,000
Lose It!	Y	Y	Y	Y	Y	4.4	55,000	2011	5,000,000
Sparkpeople	N	N A	Y	Y	Y	4.4	22,000	2012	1,000,000
MyNetDiary	N	NA	Y	Y	Y	4.5	18,000	2010	1,000,000
MyPlate	N	NA	Y	Y	Y	4.6	16,000	2010	1,000,000

Photo Based Food Entering: There are generally four ways of entering a food item into one's food log: search a textual database, scan bar code of packaged food, type free text of food name and nutrition value, and take a food photo.

The photo recording approach has the advantages of easy to use, high coverage, and promising accuracy. However, according to our study, food photo recording is not adopted in most of the food apps that are intended for nutrition analysis and health management. Among a few apps that use photos as a way to record food, most of them use the photos for social networking purpose (such as *SnapDish*) or a means to communicate with nutritionists to get manual feedbacks (*See How You Eat Diary/Coach*).

To the best of our knowledge, *Lose It!* is the only popular app that has a food image recognition function (*SnapIt*) among the food apps that have more than 1 million downloads in the Play Store. Compared to our system, *Lose It!* covers 100 types of generic food. Therefore it requires an additional step to select the fine-grained food category after the image recognition.

Using a food recognition engine that covers 100 types of specific food, a study based on *Nibble* [19] found that low accuracy in food image recognition made users revert to search based entering method. In our system, we cover 250 types of food and the number is increasing. We believe that the coverage should be targeted alongside the accuracy, or the latter will suffer too.

Portion Size Recording Methods: Determining the portion size is another key step in dietary tracking. The amount of nutrition in the food has to be analyzed based on the size of the dish. The existing approaches to size recording are done in two ways. The first is to select the size along the food name. For example, one can choose from "avocado (one fruit)", "avocado (half)", "avocado (a cup)", "avocado (50 g)" when avocado is consumed. In this approach, the portion is part of the identifier in the food knowledge database.

The second is to choose or type a number to specify the weight, the number of servings, or the volume. The problem here is that the units may not be perceived correctly, for example, some users may not know what a 100 g apple looks like.

Another problem is that the definitions of some size specifiers are not common knowledge for some people. For example, "a serving" is defined by nutritionists and it is distinct for different types of food that normal users usually do not know. In Southeast Asia context, a bowl of rice is a standard serving unit, but it is counted as around two servings of carbohydrate. *Noom Coach* tries to educate the users by using reference items to provide portion guidelines, such as one's fist is around the size of a cup and the thumb is the size of a table spoon.

Portion selection needs to be contextualized as the measuring systems may be different in different social-geometric settings. In this work, we complete the photo based entering method by proposing a portion photo based size specification method, which is more intuitive and applicable in various context.

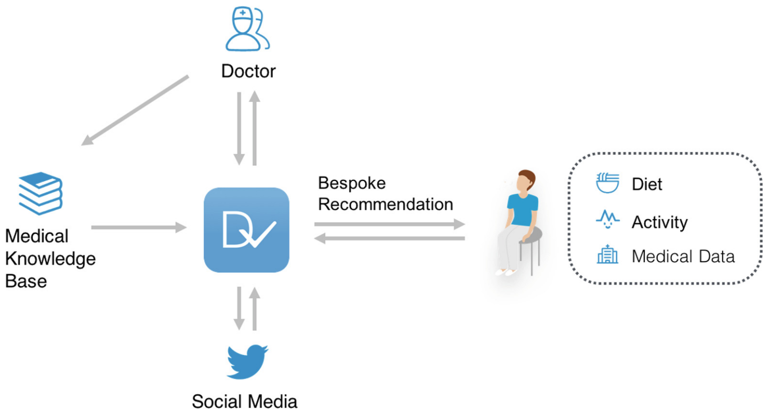

Fig. 1. Overview of system

3 *DietLens*: A Mobile App for Dietary Tracking and Management

DietLens is a prototype system that we developed for the dietary tracking and analysis application. As shown in Fig. 1, the app links users, doctors, and social media to form a computational wellness ecosystem. For users, the app will capture diet and physical activities. It may also include medical data such as chronic health conditions to complete the wellness profile of the users. The app will provide real time feedback based on users' profile and input. The knowledge base forms the basis of automatic feedback that the app pushes to the users. The users and doctor can interact through the app. The doctors will be able to manage all the users in a centralized manner. The users will also be able to interact with their friends on social media.

Figure 2 shows the main pages of the food photo taking function and the recognition result. The user is prompted to a list of candidate food names if the first one is incorrect. The back-end deep-based image recognition model can be deployed in the cloud or the mobile phone itself thanks to the development of the state-of-art deep learning algorithm [2].

In addition to the weight, serving, volume based portion selection method, we propose a reference food image based method, as shown in Fig. 3. The users need only to choose from a series of pre-compiled varying portion size photos of the food that is of the same type as the target food. The portion size photo is coded with the amount of nutrition [8,11], for example, the calories. It has been shown in [8,11] that image based portion selection maps well with the actual food intake.

Photo based portion selection requires no prior knowledge of the context: the communication is performed by comparing the standard portion size photos and the actual food. The challenge is two fold: the first is to pre-compile the portion size photos that have high coverage of the types of target food; the second is

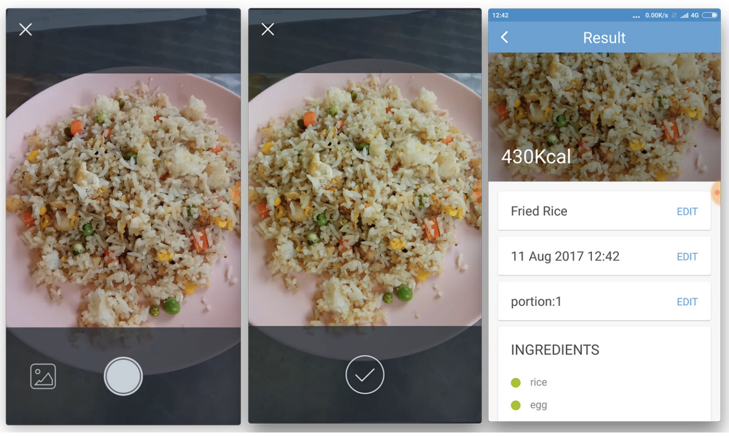

Fig. 2. Food image recognition in *DietLens*

Fig. 3. Portion selection by example food photos.

to map the actual food to a similar type of food with the portion size photos. Currently, our system covers about 60 types of food using the sliding bar portion selection method.

With the food properly logged, the nutrition databases are looked up to provide the nutrition facts. A clinically verified nutrition information database is essential. To ensure the quality and coverage of nutrition information, we resort to the following databases. The first is from a local nutrition research institute where popular local food nutrition is studied [18]. When the food item is not covered by the first, we check the Singapore Health Promotion Board [26] database of energy and nutrition composition of food. For general food items, we also use *FatSecret* API [1] as a reference.

4 Food Image Recognition Performance

4.1 Food Image Recognition Data and Method

We construct a large food data set specifically for Singapore hawker food. The data set is crawled from Google by using the food name as query. The data set contains 249 food categories, which covers most Singapore hawker food, including Chinese food, Western food, Indian food, Malay food, snacks, fruits, desserts and beverage etc. Apart from fruit images, which are obtained from ImageNet data set, most of the images in the data set were crawled from Google image search. For each category, the name was issued as keywords to search engines. We manually checked up to 1,300 crawled images in each category. We exclude images with resolution lower than 256 × 256 or suffer from blurring, images with more than one dishes, and the false positives. After this process, each category has around 300 clean images on average. In total, the data set contains 87,470 images. In each food category, 80% of images are randomly picked for training, while 10% for validation and the remaining 10% for testing. For performance evaluation, the average top-1 and top-5 accuracies are adopted.

As ResNet is the state-of-the art deep model for image classification, we adopt deep residual network (ResNet-50) [13] for food recognition. ResNet-50 contains 50 convolutional layers and 1 fully connected layers. We fine-tune the ResNet-50 on our data set. The network is trained using stochastic gradient descent with momentum set as 0.9 and the initial learning rate as 0.01. The size of mini-batch is 25 and the learning rate decays after every 8000 iterations. During the training process, we adopt data augmentation by horizontal mirroring and random cropping of input images. To prevent over-fitting, dropout is used. To evaluate the recognition performance, we report top-1 and top-5 accuracy.

4.2 Experimental Results and Analysis

Table 2 shows the recognition performances of different food groups. Compared to western food, the performances on Chinese food are much lower. This is mainly due to the facts that Chinese food have diverse appearances of dishes and wild composition of ingredients, which have been discussed in [9]. From the results, Malay food recognition is also challenging, because the food are always covered by sauces, like “sambal” and “satay sauce”. As the western food, cafeteria food, desserts and snacks are usually cooked in standard style, their performance is relatively higher. We also have an additional classifier for non-food images. For non-food image classification, the top-1 accuracy is 0.682 and top-5 accuracy is 0.861. The non-food classifier is trained on the residual images of the food categories, which are removed from the food categories and are not food. This training set is not comprehensive as it does not cover many of that non-food types.

Table 2. Recognition performances of different food groups

Groups	#Num	Top-1	Top-5	Groups	#Num	Top-1	Top-5
Chinese	78	0.642	0.879	Desserts	15	0.794	0.931
Fruit	61	0.658	0.898	Snack	10	0.769	0.954
Western	25	0.786	0.928	Indian	7	0.777	0.921
Japanese	6	0.683	0.912	Malay	40	0.611	0.889
Thai	1	0.700	0.980	Non-food	-	0.682	0.861
Beverage	5	0.932	0.984	**All**	250	0.681	0.899

Among the 249 food categories, 29 are labeled by our annotators as popular dishes, including “bak chor mee”,“black pepper crab” and “cereal prawns” etc. Table 3 presents the recognition performance on these popular food types. The average recognition accuracy are 0.752 on Top-1 and 0.931 on Top-5, which are higher than the overall averaged performances reported on Table 2.

Table 3. Recognition accuracy on 29 popular local food types.

	#Num	Top-1	Top-5
Popular food	29	0.752	0.931

The current performance on all the food and the popular food is considered satisfactory, as it is convenient to show 5 candidates as the recognition results in the mobile app. A top-5 accuracy of 0.95 and above is desirable. To further improve the performance, more training data is required. In our current model, some categories such as Chinese food have fewer training examples and hence suffer from lower top-5 performance.

4.3 Real User Photo Performance

As our experimental data was crawled from Google, the performance on real user photo may be different. To quantify the difference, we released the prototype system to the research lab which collects 100 photos taken at meal time. The accuracy on the recognized photos is 0.53 on Top-1 and 0.71 on Top-5. About 25% of user-uploaded photos are not in our food type list, which is mainly homemade food.

A set of 100 photos is too small to get conclusive insight. We thus turn to Instagram to find real user photos for testing. We crawled images from Instagram by using the food name as the queries, and manually selected those from real eating scenarios. In total, we collected 4,697 images in 94 food categories with more than 50 positive samples each. We used these categories as testing data. The comparison of performance on the laboratory test set and the real user test set is shown in Table 4. From the results, the performance on real user data is around 20% lower than that on our data set in terms of top-1 accuracy.

Table 4. Recognition accuracy on laboratory test photos and real user photos.

	Num (test image)	Macro		Micro	
		Top-1	Top-5	Top-1	Top-5
Laboratory test photos	16,349	0.681	0.899	0.703	0.910
Real user photos	4,697	0.476	0.698	0.488	0.708

A few categories that have large performance gap between our data set and Instagram are listed in Table 5. These categories include “Nasi padang”, “Breadfruit” and “Fish bee hoon” etc. The performance gap is mainly caused by two reasons. Firstly, the photo uploaded to Instagram may contain multiple dishes, while the images in our data set only contain one dish. Examples include “nasi padang” and “yong tau foo” in Fig. 4. Secondly, some dishes in Instagram are composed of ingredients different from the dishes in our data set. There dishes maybe prepared at home, like “granola” and “satay chicken” in Fig. 4.

The multi-dishes and home-made dishes are the main reasons for degraded recognition performance. In a way, it shows that food image recognition at food type level cannot capture the variation in ingredient composition. To address this issue, the addition of ingredient-level recognition is a promising approach to tackle the food recognition problem.

Fig. 4. Example images from Instagram and our data set.

Table 5. The recognition performances of 10 categories that have large performance gap between our data set and Instagram images.

	Top-1		Top-5	
	Instagram	laboratory	Instagram	laboratory
Nasi padang	0.30	0.42	0.67	0.75
Breadfruit	0.19	0.82	0.26	0.97
Satay chicken	0.21	0.58	0.72	0.95
Yong tau foo	0.22	0.53	0.45	0.76
Fish been hoon	0.24	0.48	0.76	0.87

	Top-1		Top-5	
	Instagram	laboratory	Instagram	laboratory
Lemon	0.25	0.68	0.38	0.95
Apricot	0.12	0.57	0.25	0.93
Lamb chop	0.07	0.82	0.13	0.93
Mango	0.23	0.56	0.45	0.86
Granola	0.27	0.96	0.55	0.99

5 App Usability Study

To get user feedback on the usability of the food entering method, we conducted a user study involving 15 participants, including some from the labs of the authors’ institute and some from people working in a local hospital. We assembled a list of 30 popular local food which the participants can choose as a meal that they will eat. Each participant chose to log five meals using each of the six mobile applications including ours as listed in Table 1. The food photos are hidden from the participants until they requested. This is to avoid bias towards photo based entering method.

The food logging operations of all the participants on the provided mobile phones are recorded by a screen recorder software. We checked the videos manually about the duration of operations that we are interested in and the correctness of the logged information. In total, there are 174 valid loggings after removing incomplete logging and logging by history items. The comparison is summarized in Table 6.

Table 6. Usability study on popular dietary tracking applications and our prototype system. The applications statistics can be found in Table 1.

App name	# items	Entering methods ratio	Avg. time on entering one meal (s)	Accuracy of logged food type	Accuracy of logged portion size	Percentage of logging default portion size
DietLens	45	Photo (45)	11.58	98%	85%	56%
MyFitnessPal	36	Search/barcode (35/1)	17.72	100%	78%	75%
Lose It!	23	Search/photo (19/4)	16.87	96%	63%	65%
Fatsecret	32	Search/photo/ barcode (29/2/1)	20.75	91%	57%	78%
Spark people	28	Search (28)	17.25	100%	38%	71%
Noom Coach	10	Search/barcode (9/1)	13.69	90%	57%	30%

In terms of food entering method, *DietLens* is superior in both speed and accuracy. It takes an average of 11.58 s for DietLen users to log one meal. This time is close to the speed of logging using bar code scanning based on individual records. Among the other applications, the higher the ratio of photo logging, the faster the entering speed. *FatSecret* is the slowest among all the apps, as it provides photo logging but no image recognition. Another reason is that the response speed of text search in *FatSecret* is not as good as the other applications.

For portion size selection, *DietLens* photo based approach is the most accurate as shown in Table 6. *DietLens* is the only app that provides a sample portion image approach. It is notable that *DietLens* users tend to log the portion size rather than to skip this step (the default size is logged in such case) as compared to the other applications. A subjective questionnaire which is not reported here also indicates that users prefer the example photo based portion selection method most.

In summary, the user study shows that *DietLens*' photo based dietary tracking method, including the automatic food recognition and the example photo based portion selection, provides a convenient and accurate approach for food logging and size specification.

6 Conclusions

Dietary tracking is an essential task in chronic disease management and intervention. Food photo taking and image recognition significantly reduce the burden of food entering on personal mobile devices. In this work, we have developed a dietary tracking system that applies the deep-based image recognition to accurately and efficiently log food and nutrition intake. Through real user food photo testing and user study, we found that laboratory models form the foundation of the solution but miss out some of the key challenges. The diversity of real food photos is higher than the lab trained model. An ingredient based recognition is a promising way of tracking the free style and homemade food recognition problems in which training data is sparse and not representative. Moreover, the proposed photo based portion selection method is shown to be more accurate and engages the users better than the existing methods.

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References

1. Fatsecret platform api. https://platform.fatsecret.com/api/
2. Integrating caffe2 on ios/android. https://caffe2.ai/docs/mobile-integration.html
3. Every day big data statistics 2.5 quintillion bytes of data created daily (2015). http://www.vcloudnews.com/every-day-big-data-statistics-2-5-quintillion-bytes-of-data-created-daily/
4. Singapore Health Fact: Disease Burden. Principal Causes of Death, Ministry of Health Singapore (2016)
5. Aizawa, K., Ogawa, M.: FoodLog: multimedia tool for healthcare applications. IEEE Multimed. **22**(2), 4–8 (2015)
6. Bettadapura, V., Thomaz, E., Parnami, A., Abowd, G.D., Essa, I.: Leveraging context to support automated food recognition in restaurants. In: 2015 IEEE Winter Conference on Applications of Computer Vision (WACV), pp. 580–587. IEEE (2015)
7. Bossard, L., Guillaumin, M., Van Gool, L.: Food-101 – mining discriminative components with random forests. In: Fleet, D., Pajdla, T., Schiele, B., Tuytelaars, T. (eds.) ECCV 2014. LNCS, vol. 8694, pp. 446–461. Springer, Cham (2014). https://doi.org/10.1007/978-3-319-10599-4_29
8. Brunstrom, J.M.: Mind over platter: pre-meal planning and the control of meal size in humans. Int. J. Obes. **38**(Suppl 1), S9 (2014)
9. Chen, J., Ngo, C.-W.: Deep-based ingredient recognition for cooking recipe retrieval. In: Proceedings of the 2016 ACM on Multimedia Conference, pp. 32–41. ACM (2016)
10. Ege, T., Yanai, K.: Simultaneous estimation of food categories and calories with multi-task CNN. In: 2017 Fifteenth IAPR International Conference on Machine Vision Applications (MVA), pp. 198–201. IEEE (2017)
11. Forde, C.G., Almiron-Roig, E., Brunstrom, J.M.: Expected satiety: application to weight management and understanding energy selection in humans. Curr. Obes. Rep. **4**(1), 131–140 (2015)

12. Hassannejad, H., Matrella, G., Ciampolini, P., De Munari, I., Mordonini, M., Cagnoni, S.: Food image recognition using very deep convolutional networks. In: Proceedings of the 2nd International Workshop on Multimedia Assisted Dietary Management, pp. 41–49. ACM (2016)
13. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 770–778 (2016)
14. Hingle, M., Patrick, H.: There are thousands of apps for that: navigating mobile technology for nutrition education and behavior. J. Nutr. Educ. Behav. **48**(3), 213.e1–218.e1 (2016)
15. Hoashi, H., Joutou, T., Yanai, K.: Image recognition of 85 food categories by feature fusion. In: 2010 IEEE International Symposium on Multimedia (ISM), pp. 296–301. IEEE (2010)
16. Kawano, Y., Yanai, K.: Food image recognition with deep convolutional features. In: Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication, pp. 589–593. ACM (2014)
17. Krizhevsky, A., Sutskever, I., Hinton, G.E.: Imagenet classification with deep convolutional neural networks. In: Advances in Neural Information Processing Systems, pp. 1097–1105 (2012)
18. Lau, E., Goh, H.J., Quek, R., Lim, S.W., Henry, J.: Rapid estimation of the energy content of composite foods: the application of the calorie answer. Asia Pac. J. Clin. Nutr. **25**(1), 18–25 (2016)
19. Lim, B.Y., Chng, X., Zhao, S.: Trade-off between automation and accuracy in mobile photo recognition food logging. In: Proceedings of the Fifth International Symposium of Chinese CHI 2017, pp. 53–59. ACM, New York (2017)
20. Liu, C., Cao, Y., Luo, Y., Chen, G., Vokkarane, V., Ma, Y.: DeepFood: deep learning-based food image recognition for computer-aided dietary assessment. In: Chang, C.K., Chiari, L., Cao, Y., Jin, H., Mokhtari, M., Aloulou, H. (eds.) ICOST 2016. LNCS, vol. 9677, pp. 37–48. Springer, Cham (2016). https://doi.org/10.1007/978-3-319-39601-9_4
21. Martinel, N., Foresti, G.L., Micheloni, C.: Wide-slice residual networks for food recognition. arXiv preprint arXiv:1612.06543 (2016)
22. Matsuda, Y., Hoashi, H., Yanai, K.: Recognition of multiple-food images by detecting candidate regions. In: 2012 IEEE International Conference on Multimedia and Expo, pp. 25–30. IEEE, July 2012
23. Matsuda, Y., Yanai, K.: Multiple-food recognition considering co-occurrence employing manifold ranking. In: 2012 21st International Conference on Pattern Recognition (ICPR), pp. 2017–2020. IEEE (2012)
24. Myers, A., Johnston, N., Rathod, V., Korattikara, A., Gorban, A., Silberman, N., Guadarrama, S., Papandreou, G., Huang, J., Murphy, K.: Im2Calories: towards an automated mobile vision food diary. In: 2015 IEEE International Conference on Computer Vision (ICCV), pp. 1233–1241. IEEE, December 2015
25. World Health Organization: preventing chronic diseases: a vital investment. World Health Organization (2005)
26. Health Promotion Board Singapore: energy and nutrition composition of food. http://focos.hpb.gov.sg/eservices/ENCF/. Accessed 18 July 2017
27. Waki, K., Aizawa, K., Kato, S., Fujita, H., Lee, H., Kobayashi, H., Ogawa, M., Mouri, K., Kadowaki, T., Ohe, K.: Dialbetics with a multimedia food recording tool, foodlog: smartphone-based self-management for type 2 diabetes. J. Diab. Sci. Technol. **9**(3), 534–540 (2015)

28. Willett, W.C., Koplan, J.P., Nugent, R., Dusenbury, C., Puska, P., Gaziano, T.A.: Prevention of chronic disease by means of diet and lifestyle changes (2006)
29. Yanai, K., Kawano, Y.: Food image recognition using deep convolutional network with pre-training and fine-tuning. In: 2015 IEEE International Conference on Multimedia & Expo Workshops (ICMEW), pp. 1–6. IEEE (2015)